Enhancing Real-World Applicability in Home Healthcare: A Metaheuristic Approach for Advanced Routing and Scheduling

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Abstract. We consider the home healthcare scheduling and routing problem, and we extend the classic formulation introduced by Mankowska et al, by adding several real-world features. For this novel problem, we created a new realistic dataset, and we developed a metaheuristic approach based on a combination of neighborhoods guided by a Simulated Annealing procedure. Our solver, properly engineered and tuned, is able to solve all instances in a short time. Our experimental results highlight the relative importance of the various (original and new) cost components.

Keywords: Homecare · Routing with time windows · Route synchronization

1 Introduction

Home healthcare (or simply homecare) refers to providing healthcare services and assistance to individuals in their homes rather than in a hospital or other healthcare facilities. Homecare offers a range of benefits, including personalized care, cost-effectiveness, comfort, and the promotion of independence. Depending on the individual's health needs and preferences, it can be a valuable alternative or complement to institutional care.

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Providing homecare services is an optimization problem involving scheduling and routing issues. Many problem formulations have been proposed in the literature, depending on the different settings and horizons. For an overview of the available formulations and solution techniques, we refer to the following surveys [3,4,9].

We consider here the well-known formulation proposed by Mankowska et al. [8], which comes along with a large and challenging dataset that has attracted the attention of many researchers, which dealt with it mainly using metaheuristics (see [1,2,5–7]). Although this formulation is interesting and challenging from a computational point of view, it lacks some specific features that would make the problem more attractive in reality. For this reason, we introduce hereby an extended formulation that comprises additional real-world features, i.e., multiple departure points for caregivers, incompatibilities between patients and caregivers, and working shifts for caregivers. In addition, the objective function penalizes caregiver waiting times and overtime and unbalanced workload distribution. For this novel formulation, we propose a new dataset and a search method based on Simulated Annealing, obtained by extending our previous work on the original problem [1,2]. For the formulation obtained, we created a new artificial dataset by using real road distances and sampling the relevant locations, considering the area's actual population distribution. Our search method, properly tuned, has been tested on the new dataset, highlighting which are the most impactful components of the objective function.

2 Problem Formulation

We introduce the formulation in two steps. First, we recall the basic one by Mankowska et al. [8], and then we illustrate the extensions we introduced.

2.1 Basic Formulation

The most relevant elements of the Home Health Care Routing and Scheduling Problem (HHCRSP) are:

Patients: Patients are categorized as *single service* (requiring one service) or *double service* (requiring two services, either *simultaneous* or *sequential*). Sequential double service patients require a specific minimum and maximum time gap between services. Additionally, each patient has a designated time window for starting the (first) service.

Services: Each service duration, in minutes, varies by patient.

Caregivers: Each caregiver is qualified for a specific subset of services. They begin and end their workday at the central office.

The planning horizon consists of a single day. Distances represent the travel time (in minutes) from one location to another (either a patient's home or the central office). The hard constraints of the problem are:

- Each patient must be visited during the planning horizon (either by one or two caregivers).
- A service cannot be provided by a caregiver who is not qualified for it.
- For each double service patient, the minimum and maximum time separations between the first and the second service have to be respected. In the case of simultaneous services, the separation is strictly equal to 0.
- Each double service patient needs two separate caregivers.
- A service cannot start before the beginning of the patient time window. In case of early arrival, the caregiver has to wait until the time window starts.

Conversely, it is permissible for a patient to be served late (after the end of the time window), but this tardiness contributes to the objective function.

The objective function to be minimized includes three components: *i*) the total travel time, *ii*) the total tardiness encompassing all services, and *iii*) the highest tardiness. In cases of double service patients, each service contributes separately to the total tardiness.

2.2 Extended Formulation

We now discuss the extensions that we introduced, along with their motivations from a practical point of view.

Multidepot: In some cases, it is rather unrealistic to assume that all caregivers move to the central office at the beginning of their shift. For this reason, we assume that a caregiver departs either from the central office or from their home and returns to the same place at the end of their shift. This decision is fixed in the input data and cannot be changed based on the route. In this situation, the distance matrix is extended to include the locations of all caregivers who depart from home.

Compatibility: It may happen that, for various reasons, some caregivers are not acceptable to some patients. To deal with this limitation, some patient/caregiver pairs are fixed as *incompatible* so that the given caregiver cannot serve that patient.

Waiting times: When a caregiver arrives early at a patient's home, she/he waits until the time window of the patient starts. This situation is rather inconvenient for the caregiver, but since it receives no penalty in the basic formulation, it actually occurs quite often in the solutions. For this reason, we introduce a cost component for the total *waiting time* spent by all caregivers in this specific situation.

Work shift and overtime: Caregivers are assumed to be available within the full horizon. This is rather unrealistic, as they normally work in specific shifts, which can span over the entire day (full-time), or be set either on the morning or the afternoon (part-time). Therefore, we introduce the working shift of the caregivers, so that each caregiver leaves their location at the beginning of the shift (or later) and should return by the end of the shift. If the return time is after the end of the shift, this accounts for *overtime*, which should be minimized and contribute to the objective function.

Work balance and fairness: In the basic formulation, there is no notion of work balance, causing situations in which one caregiver visits very few patients (even zero in some cases), while others visit up to ten patients. To fix this unfair situation, we introduce a measure of balance in the objective function. To this aim, we introduce the *idle time* of a caregiver, which is defined as the length of the caregiver's shift minus their working time, which in turn is measured as the service time plus the traveling time. In other words, the idle time is the waiting time defined above, plus the time before going out to the first patient, plus the time between the return to the starting point and the end of the shift (the latter only if bigger than zero). We count as fairness cost the *highest idle time* among all caregivers.

According to these extensions, we move from the three-component objective function of the original formulation to a six-component one for the new formulation, by adding waiting times, overtime and highest idle time (fairness).

These objectives might have different impacts on the quality of the solution, determining whether we give more importance to the point of view of patients or the one of caregivers and the company. In the original formulations, in order to keep the objective function simple, all components were given identical weights, thus assuming that one minute of traveling time costs as much as one minute of tardiness. We maintain this approach, applying the same weight to additional components, and defer a detailed cost analysis to future work.

3 Solution Technique

For the solution of this problem, we extend the multi-neighborhood Simulated Annealing approach proposed for the original formulation in our previous work [1,2]. This approach works on an indirect search space composed of the permutations of the patients and the assignments of the caregivers to the patients. The actual schedule is obtained by a forward greedy procedure that processes the patients one at a time according to the permutation and adds the patient at the end of the route(s) of their caregiver(s) at the earliest time.

The neighborhood relation is the combination of three atomic neighborhoods:

MovePatient: Reposition one patient in the global ordering and assign new caregiver(s) to the patient.

SwapPatients: Swap both the positions of two patients in the global ordering and the caregiver(s) assigned to them. A swap is possible only between patients with the same number of services and with current caregivers with the required abilities for the other patient.

InRouteSwap: Swap the positions of two patients within the route of a given caregiver. If one or both patients are double-service ones, the route of the *side* caregiver(s) serving the patient(s) are modified accordingly.

In order to draw a random move, first we perform a *biased* random selection to establish which of the three atomic neighborhoods should be sampled, and then a *uniform* selection within the chosen neighborhood. For the first selection, we use two parameters called σ_{SP} and σ_{IRS}, so moves of the three types are drawn with probability $1 - \sigma_{\mathsf{SP}} - \sigma_{\mathsf{IRS}}$, σ_{SP} and σ_{IRS}, respectively.

As the metaheuristic that guides the search, we make use of the classic Simulated Annealing (SA). The SA procedure starts from a random initial solution and then, at each iteration, draws a random move. This is always accepted if it is improving or sideways, whereas worsening moves are accepted based on the time-decreasing exponential distribution (known as *Metropolis Acceptance*).

SA starts with an initial high temperature T_0, which is decreased after a fixed number of samples are drawn according to the geometric cooling scheme with rate α. The search is stopped when the final temperature T_f is reached. In order to speed up the early stages of the search, we add the customary *cut-off* mechanism, such that the temperature also decreases if a fraction ρ of the moves has been accepted. The iterations saved by the cut-off are redistributed uniformly to all the remaining temperatures.

4 Experimental Results

We adapted the generator developed for the basic problem [1] and we created 500 training instances for the tuning phase plus 10 validation ones. They are available at https://github.com/iolab-uniud/hhcrsp, along with their best solutions. The tuning procedure on the training instances has been done using RACE in two stages: first the parameters of SA and then the two rates σ_*. The winning configuration turned out to be: $T_0 = 28.77$, $T_f = 0.94$, $\alpha = 0.987$, $\rho = 0.138$, $\sigma_{\mathsf{SP}} = 0.2$ and $\sigma_{\mathsf{IRS}} = 0.08$. Table 1 reports average and minimum results of 30 runs on the validation instances with the above configuration and with 100M total iterations. The table also reports the average percentage cost for each component: total distance (TD), total tardiness (TT), highest tardiness (HT), total waiting time (TWT), total overtime (TOT), and highest idle time (HIT).

Table 1. Results on the validation instances

Inst	Patients	Caregivers	avg	min	time(s)	TD	TT	HT	TWT	TOT	HIT
0	220	42	29829.8	27763	532.3	34.31	48.33	1.61	2.14	12.74	0.87
1	68	13	13776.3	13550	181.3	13.19	63.70	4.23	4.39	11.58	2.90
2	261	50	35113.6	32535	652.5	33.34	41.91	1.26	1.76	21.42	0.30
3	304	54	11119.3	10547	723.1	62.38	16.55	1.37	2.85	13.81	3.03
4	493	96	23628.1	21999	1349.6	51.95	36.34	1.39	2.85	6.78	0.70
5	233	36	25278.6	24265	518.6	22.80	59.69	1.60	1.39	14.13	0.40
6	490	87	45648.6	41273	1277.3	34.86	50.41	0.98	1.47	12.14	0.14
7	217	43	6196.4	6022	500.4	84.20	1.18	0.23	3.33	5.22	5.84
8	136	22	26517.3	25475	326.6	16.02	61.12	3.42	4.21	13.73	1.50
9	159	30	14816.3	13827	389.0	34.35	35.45	2.79	2.29	22.82	2.30

The results show that there is big variability among different instances, in terms of total cost and distribution of the cost among the various components. In particular, in some cases, the traveling cost is dominant (instances 3 and 7); in others, the tardiness component is dominant (instances 1, 5, 6, and 8). Unsurprisingly, when the tardiness is high, also overtime is relevant because some services are postponed after both the time window of the patient and the working shift of the caregiver. This reveals the presence of either a significant understaffing or a bad matching between patient needs and caregiver skills.

5 Conclusions and Future Work

We have extended a classic formulation of the homecare routing and scheduling problem, creating a novel, more realistic problem, for which we created a new dataset, properly split into training and validation instances, and a metaheuristic method based on our previous work on the original formulation [1,2].

This is a preliminary work and for the future we plan to further refine the general formulation, the cost components, and their weights, in order to capture real-world situations. In parallel, we plan to improve our metaheuristic and to hybridize it with exact methods, bringing forth a matheuristic approach.

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